A Performance Shaping Factors Causal Model for Nuclear Power Plant Human Reliability Analysis

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Abstract:

Many current Human Reliability Analysis (HRA) methods calculate human error probability (HEP) based on the state of various PSFs. There is no standard set of PSFs used in HRA, rather each method uses a unique set of PSFs, with varying degrees of interdependency among the PSFs. In calculating HEPs, interdependency is generally ignored or addressed through varying parameters in linear or log-linear formulas. These dependencies could be more accurately represented by a causal model of PSF relationships.

This paper introduces a methodology to develop a data-informed Bayesian Belief Network (BBN) that can be used to refine HEP prediction by reducing overlap among PSFs. The BBN framework was selected because it has the ability to incorporate available data and supplement it with expert judgment. The methodology allows the initial models to be updated as additional data becomes available. This paper presents a draft model based on currently available data from human error events in nuclear power plants. The resulting network model of interdependent PSFs is intended to replace linear calculations for HEPs.

Keywords: Human Reliability Analysis, human error, Performance Shaping Factors, Bayesian Belief Network,

1. INTRODUCTION

In many Human Reliability Analysis (HRA) models, the human error probability (HEP) is estimated based on a set of Performance Shaping Factors (PSFs). The term PSF encompasses the various factors that affect human performance and can change the likelihood of a human error. There are more than a dozen HRA methods that use PSFs, but there is not a standard set of PSFs used in the methods. Current HRA methods rely on sets of PSFs that range from a few to over 50 PSFs, with varying degrees of overlap (non-orthogonality) between the PSFs. This non-orthogonality is observed in almost every set of PSFs, yet current HRA methods do not offer a causal model of the PSFs. Instead, the methods that do address interdependencies generally do so by varying different multipliers in linear or log-linear formulas. These dependencies could be more accurately represented by a causal model that includes relationships among the PSFs.

This paper introduces a methodology to develop a data-informed Bayesian Belief Network (BBN) that can incorporate several types of available data and supplement the data with expert judgment. Many HRA methods cannot be easily validated because historically there has been limited, indirect data on human actions. HRA is also plagued by the subjectivity of some PSFs and the "invisible" nature of human cognition. The use of a Bayesian framework allows us to combine the available data with expert information to create a more robust form of HRA.

The proposed model development methodology uses correlation analysis and factor analysis to explore patterns of variance and suggests Bayesian techniques to link these patterns to human error. The result is a systematic way to evaluate PSFs and to define their interrelationships with respect to human performance in multiple aspects of human-machine interaction.

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This paper introduces a causal model created using a combination of expert opinion and currently available data from human error events in nuclear power plants. The data were taken from two sources: the US Nuclear Regulatory Commission's Human Events Repository Analysis (HERA) database [1] and a collection of information gathered by the University of Maryland using the Information-Decision-Action (IDA) model [2].

The model uses a PSF hierarchy developed specifically for use in causal models. This taxonomy contains a set of orthogonally defined PSFs suitable for both qualitative and quantitative analysis. The taxonomy contains PSFs aggregated from current HRA methods organized into six categories representing the major aspects of the socio-technical system. The PSF hierarchy, developed in tandem with the methodology, can be found in [3]. As additional data become available, the methodology can be used to update the model and include more detailed levels of the PSF hierarchy.

2. DATA SOURCES

There were two sources of data used in this research: the Human Events Repository Analysis (HERA) database [1] and worksheets from an application of the Information-Decision-Action (IDA) model [2]. These data sources were selected because they contained detailed information about the factors that influenced single human errors in a risk significant incident at a nuclear power plant (NPP). The selected data sources both provided detailed analyses of single human failure events; the analyses included an assessment of the state of relevant PSFs and detailed comments that provided additional information about the events. Together the two data sources provided detailed data for 158 human error events.

2.1 Human Events Repository Analysis (HERA) database

The Human Events Repository Analysis (HERA) database was developed by the United States Nuclear Regulatory Commission (NRC) and the Idaho National Laboratory (INL). It is the first database designed to collect detailed information about the factors that affect human performance in commercial NPPs. The database contains retrospective analyses of risk significant NPP operating events that contain at least one human error. The information is gathered from Licensee Event Reports (LERs), Inspection Reports (IRs) and Augmented Inspection Team reports (AITs).

There are 11 PSFs used in the HERA database; the PSFs were modeled after the PSFs suggested in the NRC's *Good Practices for HRA* [4]. The HERA database expands upon these PSFs by including specific PSF details, which provide additional information about the state of each PSF. There are over 250 PSF details that correspond to positive or negative influences on the human. During HERA coding, the analyst reviews the list of PSF details and selects the details that are relevant to the human error event. The analyst uses the PSF details to provide additional information about the state of the PSF. The state of the PSF generally corresponds to the state of the PSF details: if mostly positive PSF details are checked, the PSF state is “adequate”; if mostly negative PSF details are checked, the PSF state is “less than adequate” (LTA). If no PSF details are checked for a PSF, the state of the PSF is “nominal” or “indeterminate.”

2.2 Information-Decision-Action Model

The Information-Decision-Action cognitive model is used to analyze the behavior of NPP operators during abnormal operating conditions. The IDA model separates PSFs into internal and external PSFs. However, the focus of the IDA model is on human cognition, so the external PSF list is not as comprehensive as the internal PSF list. An updated version of the IDA model, IDAC (Information, Decision, and Action in Crew Context, [5]), expands the IDA PSFs to include a more comprehensive set of external factors and an expanded map of information flow.

Four events were analyzed in depth in [2] using the Information-Decision-Action model. Each IDA analysis contains several data sheets that provide classification information and root cause event

Table 1: Proposed tiered classification of PSFs for use in HRA causal models. When fully expanded, the set of PSFs is suitable for qualitative analysis, and the structure can be collapsed for quantitative analysis. The structure also provides a common based framework that can be expanded to deeper levels in the future. Italicized elements are behaviors / metrics associated with the parent PSF.

Organizational PSFs	Team PSFs	Personal PSFs	Situation PSFs	Machine Design PSFs
• Training Program – Availability – Quality • Corrective Action Program – Availability – Quality • Other Programs – Availability – Quality • Safety Culture • Management Activities – Staffing ∗ *Number* ∗ *Qualifications* ∗ *Team composition* – Scheduling ∗ *Prioritization* ∗ *Frequency* • Workplace adequacy • Resources – Procedures ∗ Availability ∗ Quality – Tools ∗ Availability ∗ Quality – Necessary Information ∗ Availability ∗ Quality	• Communication – Availability – Quality • Direct Supervision – Leadership – Team member • Team Coordination • Team Cohesion • Role Awareness	• Attention – To Task – To Surroundings • Physical & Psychological Abilities – Alertness – Fatigue – Impairment – Sensory Limits – Physical attributes – Other • Morale/Motivation/Attitude (MMA) – *Problem Solving Style* – *Information Use* – *Prioritization* ∗ *Conflicting Goals* ∗ *Task Order* – *Compliance* • Knowledge/Experience • Skills • Familiarity with Situation • Bias	• External Environment • Hardware & Software Conditioning Events • Task Load • Time Load • Other Loads – Non-task – Passive Information • Task Complexity – Cognitive – Task Execution • Perceived Situation: – Severity – Urgency • Perceived Decision: – Responsibility – Impact ∗ Personal ∗ Plant ∗ Society	• HSI – Input – Output • System Responses – *Ambiguity*

analysis that includes cognitive factors. The data sheets include information gathered from site visits and operator interviews. Contextual information and additional comments provided in the analysis documentation were used to assign values to external PSFs that were not included in the original IDA model.

3. PERFORMANCE SHAPING FACTOR HIERARCHY

None of the PSF sets used by current HRA methods was suitable for use in a causal model because current PSF sets were designed to be assessed by experts, not to be quantified in a model. One of the major issues with many sets was overlap among PSFs. When an expert is assessing the PSFs, the expert can mentally adjust for overlapping definitions. However, in a model it is necessary to either capture this mental adjustment explicitly or to remove the overlap. There were also additional problems with the available PSF sets. Some sets were not comprehensive, i.e., they did not include some important PSFs identified in other methods. Other sets included too many factors that could not be measured; many sets lacked any metrics that should be used to measure the PSFs, and some mislabeled specific behaviors as PSFs (e.g., Work Conduct).

We approached the mapping with the intention of dividing the final PSF set in a way that linked each PSF with a single aspect of the socio-technical system, similarly to how they are grouped in THERP [6]. The top level of the hierarchy contains five categories: machine-based, person-based, team-based, organization-based, and situation-based. This division ensures that each PSF is defined with respect to a specific aspect of the socio-technical system, which can help identify the root causes of a human error and supports definitional orthogonality. The addition of a hierarchical structure allows us to maximize the use of the data by propagating data through the model.

The final PSF set for use in causal modeling is presented in Table 1. The set was developed by aggregating information from multiple PSF sets and then refining them into a single set that is comprehensive, orthogonal, and measurable. The aggregated PSF information was merged with the expansive list of HERA PSF details and then reorganized into a structured PSF hierarchy based on the IDAC model. In the IDAC model the PSFs are defined orthogonally, but they are not necessarily independent. The IDAC model offers qualitative links between PSFs that can be seen as the beginning of a directed model. Further details about the development of the PSF set are provided in [3].

4. MODEL DEVELOPMENT

This section summarizes the procedure for creating a quantified causal model of relationships among PSFs. A full description of the methodology can be found in [3]. The methodology can be applied in its entirety to create a data-driven model linked to human error events. The procedure can also be modified to create a mixed expert/data model by applying step 1 to identify which variables can be included quantitatively and then using expert information to augment the model.

The current methodology assumes that PSFs have two states (Adequate and Less Than Adequate (LTA)) because this is the form of current data. Given additional levels of discretization, the methodology will start by identifying and merging similar PSF states (e.g. totally inadequate, partially inadequate) for each PSF and then proceed to identifying and merging similar PSFs. Suggested threshold values are based on the currently available data and may be adjusted as additional data becomes available.

4.1 Model Development Tools

4.1.1 Bayesian Belief Network

The basic form of the causal model is a Bayesian Belief Network (BBN) directed acyclic graph. In a BBN, each variable is represented as a single node. Relationships between nodes are indicated with directed arcs. Once all arcs are drawn, each node is assigned a marginal or conditional probability table. These probability tables contain all known information concerning the state of the system based on both expert opinion and available data. In a BBN, each node is assigned a probability distribution based on the possible states of its parent nodes. Each node in a discrete BBN has a finite number of possible states. Many BBNs use binary nodes, where 0 and 1 represent the positive and negative states of the node. The sum of the marginal probabilities of all states within the same node must equal 1.0. Each possible state of a root node is quantified with the marginal probabilities of the states. Once each probability distribution is set, the initial model is complete. As new information becomes available (e.g., evidence about the state of one node), the probabilities of all nodes in the model can be automatically updated based on the evidence.

The fully quantified BBN represents the prior knowledge for an analyst. To use the model, the analyst will make observations (set evidence) about certain nodes and examine the impact on specific nodes of interest. By setting evidence, an analyst is proving new information to inform the model. This produces updated probabilities for all nodes in the model. Analyst evidence is often the observation of a particular state of a node. The analyst sets the evidence in the BBN and the network updates probability of each node based on both prior observations and new evidence. For nodes where there is no evidence, the network relies on the prior probability. Once the BBN is complete, it can be incorporated into a PRA by linking BBN nodes to other risk models [7].

4.1.2 Polychoric correlation analysis

To create the base structure of a model it is necessary to determine how the nodes of the model relate to each other. The relationships between the nodes in the model are determined based on the correlation of the PSFs. Correlation gives a quantitative measure of similarity between two variables – the amount of variance from the common area between them – thus garnering an initial understanding of the variable relationships. The correlation is indicated by a number between -1 and 1. A correlation of 0 indicates complete independence between the variables, and a correlation of 1 indicates a perfect increasing linear relationship.

Several different correlation techniques can be used to develop a pair-wise correlation matrix. For normally distributed data, Pearson product moment correlations can be obtained using most commercial software packages. If data is not normally distributed, product-moment correlation values are not valid. Discrete data is not normally distributed, but the underlying process creating the data may be. For discrete data representing a latent continuous variable, polychoric correlation should be used [8]. The fundamental assumption underlying polychoric correlation is that discrete data is representative of an underlying normally distributed model and that somewhere in the model there are thresholds where the variable changes states.

When using binary data such as the data from IDA and the HERA database, tetrachoric correlation, a specific case of polychoric correlation, should be used. Determining tetrachoric correlation is a computationally intensive task. Polychoric and tetrachoric correlations can be calculated in SAS by using the %POLYCHOR macro [9].

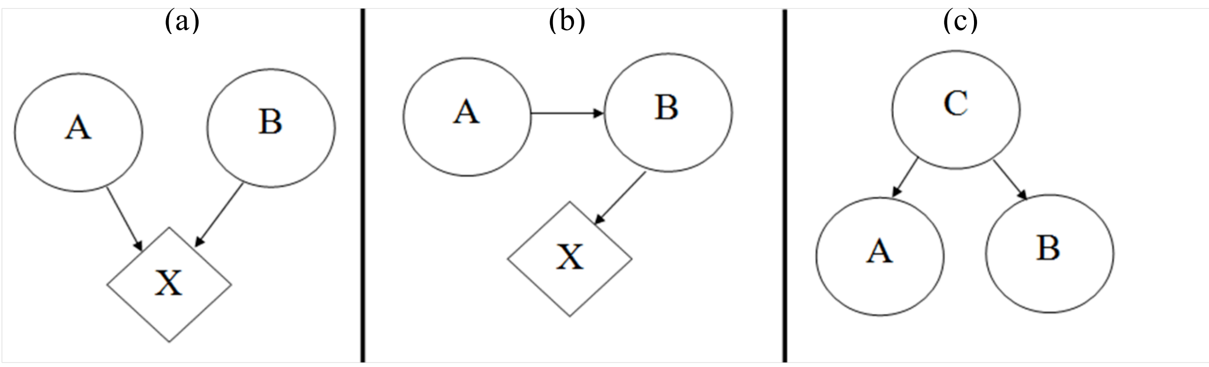
4.1.3 Factor analysis

Factor Analysis is a family of multivariate techniques used to identify relationships among the variables and to identify underlying or latent influences. This is accomplished through evaluation of patterns of variance in the data. Variance is effectively a measure of deviation (variation) or spread of the data. In terms of human action, variance is the difference between observed behavior and expected or average behavior.

Factor analysis can be used to discover relationships among multiple PSFs and between PSFs and error. The basic assumption of FA is that there are underlying influences in the data, and that these underlying influences manifest in patterns of variance that move together. For discrete data, such as that in the HERA database, the Minres (MINimum RESiduals) FA technique is appropriate [10]. The Minres technique is an unweighted least squares method that seeks to minimize the sums of squares of the residual matrix, so the suggested factors explain the maximum amount of variance in the correlation matrix. This is an iterative process wherein factors are estimated based on the initial communalities and the communalities are then updated based on the results and the process repeats.

Interpretation is the most critical step in any FA. An analyst must give meaning to the factors to transform them from abstract numerical concepts to meaningful constructs. Analysts should explore several different factor models to determine which factors best fit their application. Without interpretation, the factors are simply patterns in data. In a data set there can be several explanations for observed patterns of variance. Assuming that there is no overlap between any of the PSFs that would affect the variance, all observed variance must be due to some kind of relationship between the PSFs. Figure 1 contains graphical representations of three potential causal relationships between PSF A, PSF B, and outcome X (i.e., error). In Figure 1a, PSFs A and B are independent of each other, but they both directly influence the outcome; they have a common child node. In Figure 1b, PSF B directly influences the outcome, and PSF A indirectly influences the outcome through PSF B. In this relationship we expect to see the variance move together because A causes (or is a condition for) B. In Figure 1c, A and B may or may not influence the same child node, but they still vary together because

Figure 1: Possible causal relationships between two PSFs (A and B) and an outcome (X).



they share a parent node.

Interpretation of factor results provides preliminary groups of Error Contexts for specific work tasks. All sub-events used in this analysis are XHE events, i.e., known failures. We are adapting FA to interpret these underlying influences as visible manifestations of failure rather than invisible human performance.

4.2 Error Contexts

High correlations suggest only that two specific PSF groups have been observed together in the human error events analyzed, but these correlations do not offer insight into *why* relationships exist among PSF groups. High correlation may indicate that the nodes are not orthogonally defined, that two nodes have a causal relationship, or that the nodes have a common parent or child node. High correlation may also indicate that the PSFs have a synergistic effect on error; we call this synergistic effect an Error Context.

Error Contexts (ECs) are patterns of variance identified by factor analysis; each factor (eigenvector) retained from factor analysis forms one EC. Patterns of variance identified through FA are traditionally labeled "latent variables." Since we are analyzing only human failure events (XHEs) from HERA and IDA, the observed patterns can be viewed as visible manifestations of the context underlying the error. This interpretation is justified for factors with eigenvalues greater than 1.0. An eigenvalue greater than 1.0 indicates that its eigenvector accounts for more than its proportional share of variance. Each factor is a group of PSFs that contributes more to human performance errors than would each PSF if acting alone; the whole (factor) is greater than the sum of its parts (PSFs).

4.3 Model Development Procedure

The model development methodology suggested is based on discrete data similar to the data available in the HERA and IDA events. Suggested cut-off values should be adjusted for different data sets after considering the amount of data and statistical significance of results. For a more detailed version of the full methodology, see [3].

1) Determine which PSFs will be included in quantitative analysis.
   a) Start with the expanded PSF hierarchy (Table 1) and collapse the PSFs:
      i) Identify PSFs that are LTA in fewer than 10% of the sub-events. Merge these PSFs with one or more PSFs at the same level of the hierarchy, or collapse the category.
      ii) Identify PSFs that are LTA in greater than 90% of the sub-events. Expand these PSFs into one or more sub-levels.
      iii) Run correlation analysis on PSF set. Identify outliers (PSFs producing several correlations $> |0.95|$). Merge with one or more PSFs.
      iv) Run factor analysis on PSF set. Identify PSF producing the largest Heywood case and merge with one or more PSFs. Repeat this step until all Heywood cases are eliminated.
2) Draw directed arcs between PSFs with correlations $> |0.3|$.
   a) Direction of the arc is based on expert information about the direction of causality.
   b) Arcs may be omitted between the PSFs if the correlation is judged to be the result of parent, child, or EC relationships in the model.
3) Identify ECs and draw arcs between PSFs and ECs
   a) Run several FA models on PSF set.
   b) Apply FA stopping criteria to determine appropriate number of factors.
   c) Include each factor as an EC in the final model. Draw arcs from each PSF included in the factor to the EC node.
4) Populate marginal and conditional probability tables.

5. CAUSAL MODEL OF HUMAN ERRORS IN NUCLEAR POWER PLANTS

The ultimate goal of model development is to develop a large model containing all of the PSFs in the second and third levels of the hierarchy. However, with the amount of data currently available we cannot produce valid, convergent factor analysis results on the entire PSF set. To determine the set of PSFs used in the final model, the PSF hierarchy was collapsed as indicated in the methodology. In order to retain information from the data, PSFs were merged together instead of completely eliminated whenever possible.

The final PSF set contains the 9 elements that had sufficient data to be included in the model and that provided convergent factor groupings with correlations below |1.0|. The correlations among these 9 PSFs are suitable to quantify a causal model, and the factors output by FA are also suitable to be included in the model. The PSF set is presented in Table 2.

Table 2: The 9 PSFs used in the final causal model

Model Node	Included PSFs
Training	Training
Org. Culture	Safety Culture, Management Activities, Corrective Action Program
Resources	Procedures, Tools, Necessary Information
Team	Communication, Team Coordination, Team Cohesion, Direct Supervision, Role Awareness
Attitude	Morale/Motivation/Attitude, Bias, Attention
Knowledge	Skills, Knowledge and Experience, Familiarity with Situation, Physical & Psychological Abilities
Machine	Human-System Interface, System Responses
Loads/Perceptions	Task Load, Time Load, Other Loads, Perceived Situation Severity, Perceived Situation Urgency, Perceived Decision Responsibility
Complexity	Task Complexity, Hardware & Software Conditions

5.1 Model Structure

Each of the 9 PSFs became a single node in the final model. After collapsing the PSF hierarchy down based on available data, we ran tetrachoric correlation analysis. The correlation table is presented in Table 3. We used a value of |0.3| as the cut-off correlation for a relevant relationship between PSFs; arrows were drawn between pairs of PSFs where a causal relationship exists.

There are some correlations that could not be explained by a causal relationship between the PSFs. For example, *Complexity* shows high correlation with *Team.* To explore these relationships, we ran several exploratory factor analyses on the 9 PSFs and compared the results. We ran Principal Factor Analysis and Minres factor models for between 1 and 5 factors. We selected the 4-factor model based on the eigenvalues of the resulting factors and the shape of the scree plot. The screen plot showed discontinuity after the fourth factor. For the PFA, the first four factors had eigenvalues greater than 1.0. The fourth factor in the Minres results has an eigenvalue of 0.98, but we elected to retain this factor based on the scree plot and the PFA eigenvalues. In both PFA and Minres FA, the four-factor model had a highest p value of the five models tested. Table 4 contains the Minres FA results for the 9 PSFs.

The model contains a node for each PSF and each EC. Arcs were drawn between PSFs with correlations above |0.3| with a causal relationship supported by expert information. Relationships that can be explained causally are explained in this section. Relationships that do not have an obvious causal link are explained in Section 5.2. The causal model is presented as Figure 2.

Table 3: Tetrachoric correlation values used to develop the structure of the 9-Bubble Model

	Training	Org. Culture	Resources	Team	Attitude	Knowledge	Machine	Loads / Perceptions	Complexity
Training	1								
Org. Culture	0.151	1							
Resources	0.274	0.029	1						
Team	0.373	-0.025	0.094	1					
Attitude	0.036	0.152	0.006	0.094	1				
Knowledge	0.042	-0.116	-0.086	-0.073	-0.434	1			
Machine	0.089	-0.384	-0.029	0.179	0.004	0.072	1		
Loads/Perceptions	0.514	-0.254	0.170	0.449	0.305	0.076	0.319	1	
Complexity	0.331	-0.319	0.343	0.354	0.082	0.100	0.205	0.463	1

Table 4: Minres factor analysis results for the 9 PSF groups.

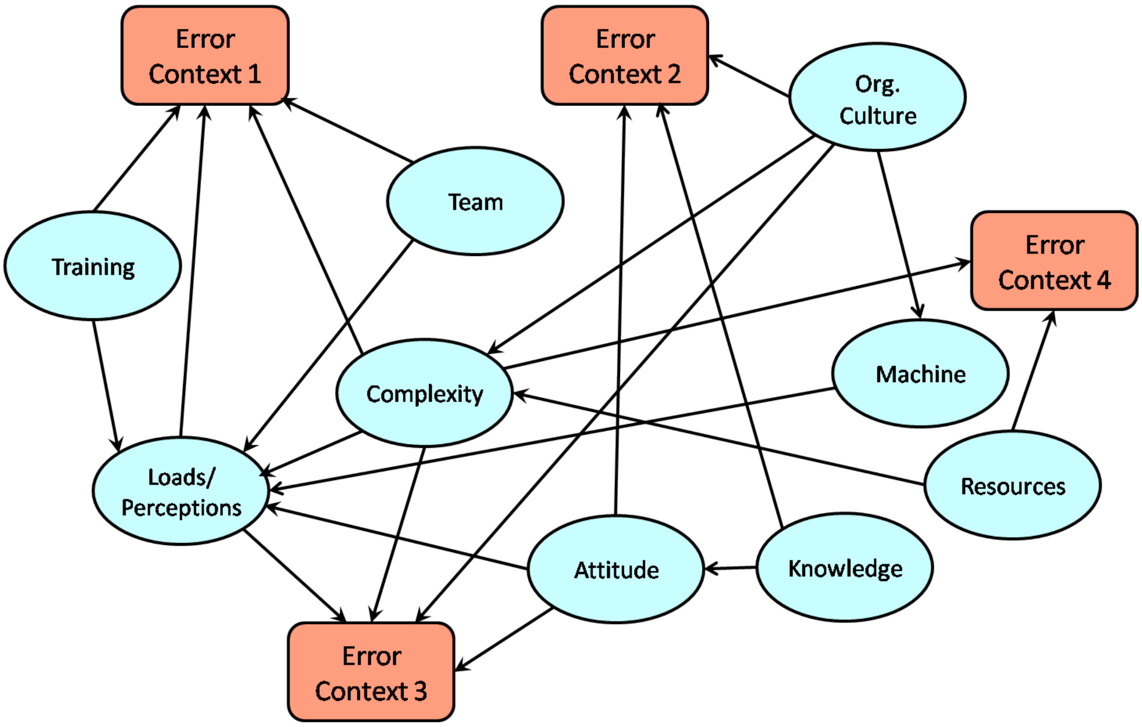
	EC1	**EC2**	**EC3**	**EC4**
Training	0.67			
Org. Culture		0.75	−0.65	
Resources				0.98
Team	0.54			
Attitude		0.74	0.64	
Knowledge		−0.37		
Machine				
Loads/Perceptions	0.72		0.45	
Complexity	0.41		0.35	0.34
Eigenvalues	2.58	1.63	1.27	0.98

There are numerous causal arcs into *Loads/Perceptions*. There are high correlations between *Loads/Perceptions* and *Training, Team, Machine, Complexity*, and *Attitude*. Each of these correlations has been interpreted as a causal contributor to *Loads/Perceptions* because they all directly affect the way personnel perceive the situation. This is because perceptions and loads are the worker's personal assessment of the scenario, including the machine, the team, and the situation. Intrinsic worker attitude also causally contributes to the individual's loads and perceptions because the characteristics that manifest as attitude also affect individual perception.

The causal arrow from *Knowledge to Attitude* represents a negative correlation. The arrow implies that adequate knowledge contributes to less than adequate personal attitudes, or that LTA knowledge contributes to adequate attitudes among personnel. This can be seen in situations where experienced personnel use work-arounds (non-compliant attitude) to deal with a situation. Less experienced personnel may not know as much about the system and therefore may not be able to develop work-arounds for the system. They must rely on available resources and tend to approach a situation more cautiously to compensate for their reduced knowledge. This effect is observed in HERA event [11] an experienced worker violated emergency operating procedures that require reporting system state to the US NRC: "The shift supervisor relied on his memory of determination/notification requirements rather than check any procedure (XHE8)." A less experienced worker may have avoided making this error, because LTA knowledge about the situation would force the worker to consult the procedure.

The causal arcs from *Organizational Culture* to *Machine* and from *Organizational Culture* to *Complexity* represent a negative correlation. The negative correlation here could be partially due to the effect of safety culture on the HERA data; organizations with good organizational culture tend to be more willing to report problems with the machine or may more accurately report the complexity of a situation. So the causal arrow in the model does not necessarily imply that adequate *Organizational*

Figure 2: Causal model of PSFs linked to human error events in nuclear power plants



Culture causes inadequate machinery or complexity, rather that adequate *Organizational Culture* causes increased reporting of inadequate machinery and complex situations. Additionally, organizations with inadequate machinery must be more attentive to the machinery and thus benefit from a positive organizational culture. As additional data becomes available, further analysis should be done to determine the nature of the relationships indicated by these links, or if this link is the result of underrepresentation of machine factors in the data.

The causal arrow from *Resources* to *Complexity* is logical, because lack of resources results in additional complexity. This can be seen in situations where there are inadequate procedures. Inadequate procedures may contribute to complexity in several ways. When there are no procedures for a situation, the required actions are knowledge based. Knowledge- based actions are more complex than rule-based actions. Extremely complex situations are also more likely than routine situations to be outside the scope of procedures. However, we cannot draw a causal arrow from resources to complexity based on this logic, because the complexity of the situation doesn't necessarily cause the lack of procedure.

5.2 Discussion of Error Contexts

The first error context is the set of *Training, Team, Loads/Perceptions,* and *Complexity*. The PSFs contributing to this EC have the most significant impact on error because this is the most significant. The first factor's eigenvalue is much larger than the eigenvalues of the other factors; it accounts for the greatest amount of variance in the sample. The relationships among these PSFs suggest several things about how errors occur in NPPs. The inclusion of *Hardware & Software Conditions* (merged into the *Complexity* node) as one of the contributors is significant since humans typically do not have the opportunity to commit an error if they are not interacting with the plant. During normal operating conditions the plant operates with minimal human intervention. Operators monitor plant conditions until an abnormal occurrence, i.e., a conditioning event, which requires the operating crew or maintenance personnel to interact with the plant.

The relationship between *Hardware & Software Conditions* and *Complexity* is a causal relationship – a degraded machine state typically causes the situation to become more complex. One example of a conditioning event increasing situation complexity can be seen in [12], where an EDG trip occurred during a LOOP event. Other influences that affect *Complexity* include *Teamwork* and *Training.* A well-functioning team can reduce the perceived loads and the situation complexity by efficiently organizing and dividing tasks. Training can contribute to the proper functioning of the team and also contributes to personnel knowledge, which affects how a person perceives the load and the complexity of the situation.

The second error context is *Organizational Culture, Attitude,* and *Knowledge.* The LTA states of *Organizational Culture* and *Attitude* are positively correlated with the EC, and LTA *Knowledge* is negatively correlated with it. This suggests that LTA *Knowledge* is not a contributor to this "type" of error. Rather there is not inadequate knowledge; we can't say that the people are particularly knowledgeable, but they do not lack necessary knowledge. The combination of adequate *Knowledge* with LTA *Attitude* suggests that the attitude of the worker plays a major role in errors committed by experienced personnel. The data support the theory that workers with less knowledge or experience tend to compensate for their inexperience by working more carefully. Experienced personnel are prone to making mistakes due to carelessness or poor work practices, including compliance and prioritization behaviors. Poor work practices are rarely limited to one member of an organization; rather, LTA *Organizational Culture* creates an environment that allows worker attitudes to decline.

The third error context is *Organizational Culture, Attitude, Loads/Perceptions*, and *Complexity.* The fact that both *Loads* and *Complexity* load on this factor is logical – a more complex situation will increase perceived loads. Likewise, the number of simultaneous tasks (actual loads) can also increase complexity. *Attitude* plays a role in how situations, especially complex situations, are translated into perceived loads. *Organizational Culture* has a negative correlation with this PSF, which suggests that this factor is linked to adequate organizational culture. This is likely because the second error context (which has a higher eigenvalue and thus explains more of the variance) absorbs most of the situations where *Organizational Culture* is LTA.

The fourth error context is *Resources* and *Complexity.* This is the least important factor, which suggests that inadequate resources are not seen alone in many errors. Again this EC is linked to *Complexity*, which is logical because complex situations may be unfamiliar to personnel and thus personnel rely on the resources, especially procedures, more heavily.

Machine does not loan on any of the factors and therefore does not appear in an error context. This is logical because of the generally unchanging nature of HSI; workers accept the system as it is designed. Operators tend to compensate for system shortcomings, e.g., they develop workarounds to deal with bad display. Maintenance workers also develop workarounds, e.g., a worker who must enter a narrow space between display panels might turn sideways to avoid bumping into a panel.

The quantitative analyses support many relationships already theorized to exist. It is interesting to note that *Complexity* loads on the first, third, and fourth factors, which suggests that complexity is an important contributor to human error. Complex situations may include failures of multiple system components, failure masking (e.g., failed sensors that obscure hardware failures), and unanticipated plant conditions. These complex situations may be outside the scope of worker training and available procedures, so worker behavior shifts from rule-based to knowledge-based, which increases the likelihood of error.

5.3 Model Quantification

This section contains the conditional probability tables for the 9 PSFs in the model. All of the probabilities are conditional on the error and a risk significant scenario (RSS),

$$P(PSFs \mid (Error \cap RSS)) \tag{1}$$

The marginal probability of each state (k) of PSF i was assessed using the relative frequency of the state, for n sub-events: (2)

$$P(PSF_i = k) = \frac{n_k}{n}$$

For root nodes, the marginal probabilities fully specify the conditional probability table. For nodes with one, two, or three parents, the conditional probabilities are assessed using marginal probability of the child and each parent, the correlation between the nodes, and a set of linear equations provided in [3].

Training

LTA	0.37
Adequate	0.63

Knowledge

LTA	0.53
Adequate	0.47

Org. Culture

LTA	0.48
Adequate	0.52

Team

LTA	0.46
Adequate	0.54

Resources

LTA	0.40
Adequate	0.60

Loads/ Perceptions[1]

LTA	0.41
Adequate	0.59

Machine

Org. Culture	LTA	Adequate
LTA	0.36	0.62
Adequate	0.64	0.38

Attitude

Knowledge	LTA	Adequate
LTA	0.47	0.87
Adequate	0.53	0.13

Complexity

Org. Culture	LTA		Adeq.	
Resources	LTA	Adeq.	LTA	Adeq.
LTA	0.62	0.50	0.57	0.52
Adequate	0.38	0.50	0.43	0.48

Conditional probability tables for the Error Context nodes will have to be assessed using expert judgment until there is more data about the PSFs affecting human success events. The HERA database has the framework to collect this data, but the current success data is not suitable for analysis because the retrospective information sources provide very few details about non-error events. Quantification of the EC nodes is discussed further in [3].

6. CONCLUSION

This paper introduces a methodology to create a causal model of relationships among PSFs. There are several possible applications for causal models of relationships among PSFs that are linked to human error:

- The model could be integrated into HEP calculations to provide more informed HEP estimates by considering interdependencies among PSFs instead of treating them as independent entities. The quantitative aspects of integration are discussed in [3].
- The model can be used to assess the benefits of different risk reduction efforts before they are implemented.
- The model can be used for informed error management, e.g., to understand and compensate for known weaknesses in the system while long-term actions are planned.
- The model can be used to identify potential variables to manipulate in simulator training or data collection experiments.

Since HRA is a discipline that involves understanding human performance it is difficult to create and validate a model. Models are largely based on expert opinion and there are no HRA benchmarks that

[1] The Loads/Perceptions PSF has five parent nodes and thus has a large number of linear equations that must be solved to completely specify the conditional probability table. We have elected to give Loads/Perceptions a uniform distribution equal to its marginal probability distribution until more data becomes available.

can be used to validate these models. We have created a modeling approach that uses available data to provide a level of validation to the model. Using both expert opinion and available data in the same model provides a level of validity greater than any current HRA model.

The BBN provides a natural framework to assess the benefit of alternative risk reduction strategies or to provide more informed error management. Analysts can use the BBN to record the known state of a PSF and then update the probabilities of the other nodes in the model. Similarly, the analyst can compare different risk mitigation efforts by making observations in the model and seeing how they affect the likelihood of human error. In both situations the analyst can then see which PSFs have the most significant change in probability. Analysts can model different combinations of PSF states to see which system elements have the greatest impact on overall system risk and then identify risk-significant system weaknesses before they result in errors. By evaluating which model nodes have the most significant probability changes, the analyst can better direct their resources at system elements that have the greatest risk impact.

Acknowledgements
The authors would like to thank Dr. Erasmia Lois and Dr. Y. James Chang for support throughout this project. This work was supported through a Collaborative Research Agreement between the US Nuclear Regulatory Commission and the University of Maryland Center for Risk and Reliability. The opinions provided in this paper do not represent the views or positions of the U.S. Nuclear Regulatory Commission or the U.S. Government.

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